Review Article

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Detection of Weeds in Cotton Farms Using Mobile Net– Single Shot Detector

Rajasenbagam T* and Hari Krishnan G

Department of Computer science and engineering, Government college of Technology, Coimbatore.

***Corresponding Author**
Rajasenbagam T, Assistant professor, Department of Computer science and engineering, Government college of Technology, Coimbatore.

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Abstract
In recent years, the automated weed control systems used for prevent the growing weeds from main plant in order to improve the productivity. The researchers put on more efforts to identify the location and amount of the weed area in the land by the automated manner. Deep learning provides the way of finding the location of the object by using of object detection algorithms. In this research focus on the identification of the weeds in the cotton fields by drawing bounding boxes using MobileNet-Single Shot Detector object detection algorithm. From the obtained results it has shown as 70.1% Average Precision(AP) for detection on weeds.

Keywords: Deep Learning, Object Detection, Single Shot Detector, Average Precision.

1. Introduction

In recent years precision agriculture has become more popular due to it improves the productivity of the plant by using of the advanced automatic methods. Weeds are the unwanted plants growing around the crops that are not controlled by natural. Wang [1] claims that weeds directly compete with crops for nutrients, water, and sunshine, resulting in output losses of an average of 34%. Weeds are further more difficult to spot because of their uneven distribution and overlap with other crops.

Manual weeding is the oldest method of weed management in crops. It is labor- and time-intensive, though, which renders it ineffective for larger-scale crops. Chemical and, to a lesser degree, mechanical weeding technologies are used in agriculture today, but in our region (the Andean Highlands), 75% of the crops produced, such as lettuce, require hand weeding, which increases production inefficiency and costs [2]. Furthermore, there is a huge margin for error when it comes to weeding, and these methods run the risk of harming the plants.

To address this issue, the notion of site-specific weed control, which refers to detecting weed patches and spot spraying or mechanical removal, was developed [3]. Weed removal early in the season is crucial since weeds would fight for resources with the crops during the vital growth stage, potentially resulting in yield loss. Early season weed detection that is accurate and timely aids in the generation of prescription maps for the site-specific use of post-emergence herbicides [4].

Computer Vision was the first approach for object categorization and detection. These technologies incorporate digital image processing algorithms for processing weed photos and extracting characteristics from them.
Deep learning is a subclass of machine learning in which the learning algorithms incorporate artificial neurons that imitate the human brain. Once the object has been recognized by the system, it must be eliminated using the automated weed control system. This requires locating the exact position of the weed. The system employs object detection techniques such as RCNN, Faster RCNN, YOLO, SSD, and others for this localization process. It should be emphasized that object detection algorithms require images, labels, and bounding box co-ordinates.

The remaining structure of this paper presented below. Section 2 gives the literature review of the previous weed detection task. Section 3 gives the complete architecture of proposed methodology and its steps. Section 4 presents the obtained results and discussions. Finally, section 5 concludes this proposed work and suggests some future enhancements.

2. Literature Review

Use this document as a template by simply typing your text into it. Shaun M. Sharpe et al. [5] proposed detecting goose grass in strawberry and tomato crops. They employed the Tiny-YOLO-v3 detection technique for the object detection job, and the model's performance will be measured using the F-score. For strawberry and tomato crops, the proposed approach yielded 0.75 and 0.56, respectively.

Using several techniques of object detection, Kavir Osorio, et al. [6] carried out the localization of weeds present in the lattice crops. All photos are aligned and corrected for fisheyes as part of the preprocessing process, and the finished photos are then fed into the following models.

The Histogram of Gradients (HOG) is used to employ gradients to extract features from a picture. It was mostly utilized to generate the mask using the OTSU and NDVI methods. The pre-trained Support Vector Machines (SVM) are then employed for the categorization of the lattice and the marijuana, and they produce the mask that is used to produce the cannabis potion. When the created mask is multiplied by the original picture, the position of the weeds is revealed. Also YOLO-v3 and Mask RCNN has been developed by the author. From the obtained results, Mask R-CNN gives the better results compared to others.

In [7] suggested different object identification methods for detecting weeds in soybean farms. UAVs capture the photos, which are then manually labeled for ground truth boxes. Patch Based CNN, Faster R-CNN, and SSD (Single Shot Detector) algorithms are fed images and annotations. According to the results, the SSD outperforms other approaches.

For the detection of weeds in the corn and soybean plant, the authors Aanis Ahmad, et al., [8] utilized a variety of pre-trained models. For this study, they made use of the Deep Weeds open source dataset. They employed the YOLO-v3 method, which is used to detect objects. The findings indicated that the YOLO algorithm provides 54% of mAP. One of the significant points of this study is that the models were trained using both the PyTorch and Keras libraries.

The object detection model described by Shaun M. Sharpe et al. [9] for detecting weeds in Florida food crops. For this study, they used both in-discriminate (one class) and discriminate (three classes) vegetation that is often grown in Florida. The YOLO-v3 object detection model is used in the proposed methodology. The results suggest that the model is effective at detecting vegetation.

3. Proposed System

The overall workflow of the proposed system has been shown below figure 1.

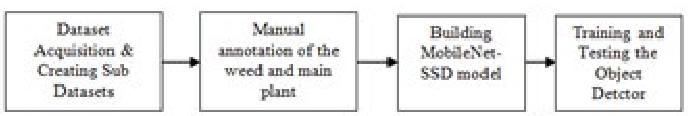

Figure 1: Overall Workflow of the Proposed System

3.1 Dataset Collection

For this research, the CottonWeedID15 dataset was utilized. The dataset was acquired from the https://www.kaggle.com/yuzhenlu/cottonweedid15 website and is free source. 5187 RGB images of 15 weeds that are frequently found in cotton fields in the southern U.S. states make up the dataset CottonWeedID15. Digital cameras on handheld devices or cellphones were used to capture these images. Images were taken in 2020 and 2021 at various sites around the U.S. cotton belt states, during various phases of weed development, and under natural field lighting conditions to ensure image variety. Scientists that specialize in weeds and skilled persons manually identified the images.

For this work, there will be only 4 types of weeds has been considered and that will be processed by our system. Those are Carpetweeds, Eclipta, Morning Glory and Ragweed.

But one of the disadvantage of this dataset was, doesn't contains the main plant image. It leads to when the model was trained for weeds only. It doesn't classify the main plant images.

The main contribution of this work was capturing the real time images of the main plant i.e. cotton. So this modified dataset was used for the detection task. So including cotton there are 5 classes are present in this research problem. From this modified dataset, there was selected two sub datasets due to object detect algorithms take longer time for training and inference, the minimal amount of dataset was considered. The number of images available in the sub datasets mentioned below in Table 1

	Sub Dataset 1	Sub Dataset 2
Training Set	36	35
Validation set	22	17
Total	58	52

Table 1: Distribution of images in the Sub-Dataset

3.2 Image Annotations

For the object detection task, it must be requiring the ground truth boxes to denoting the location of the weed and cotton. So the images must be annotated manually using any of the annotation tools. For this research, Label Img tool was used for the manual annotation process. Labl Img tool was developed by Python and QT Console. The sample annotation of the image shown as given figure 2(a). Save this annotation file in Pascal VOC format which was acceptable format for the SSD Object detection algorithm. The annotations are saved in the .xml file which contains the bounding box positions and label of the image. Sample annotation file (img_file_name.xml) shown in figure 2(b).

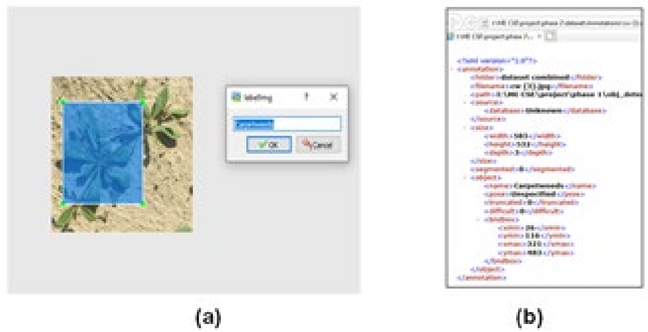

Figure 2: Manual Annotation of Images by Label Img tool

All sub-dataset images are manually annotated using this tool and save in the corresponding folder.

3.3 Mobile Net-SSD Object Detector

When employing multi box to detect numerous things present in a picture, single shot detectors like YOLO only need one shot.

According to the figure 3 the MobileNet base network for SDD is a conventional CNN design for high quality image classification but lacks the final classification layers, SSD features a basic MobileNet network followed by multi box convolution layers. As a result, it is utilized to extract features, and further convolution layers are employed to detect objects.

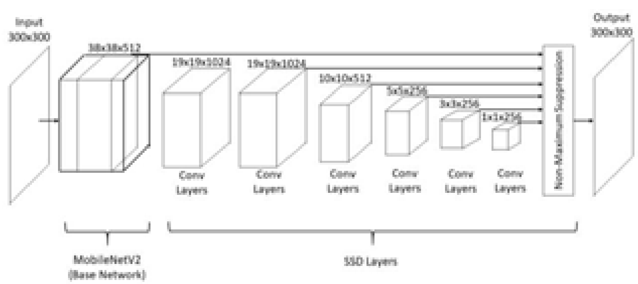

Figure 3: Single Shot Detector (SSD) Architecture

Its high-accuracy object detecting technique is substantially faster. Using numerous boxes or filters of various sizes and aspect ratios for object detection allows for high detection accuracy in SSD. These filters are also applied to various feature maps from a network's subsequent phases. This facilitates detection at various scales.

4. Results and Discussion

The images with its annotations are fed into the downloaded MobileNet-SSD model and trained it much iteration. After several iterations, the model evaluated the validation images and produces the performance metrics. In this work, Average Precision (AP) has been used for the evaluating the model. Normally Average Precision calculated at the threshold of Intersection over Unit (IoU) = 0.50 of 0.90.

In this work, there are 2 sub-datasets created, trained and validated by the model. The model has been configured as 2 types based on the number of steps or iterations. The obtained results are tabulated below in Table 2.

Iterations	**Average Precision (%) When IoU=0.50**	
	Sub dataset 1	**Sub dataset 2**
5000	70.1 %	62.2%
10000	58.7%	59.3%

Table 2: Performance Metrics of MobileNet-SSD

From the above table, it clearly shows that SSD model performs well for the sub-dataset-1 with 5000 iterations. When new unseen test image tested against the proposed object detector, it predicted the locations of the weed by the bounding boxes with the confident scores. See the figure 4 for the results.

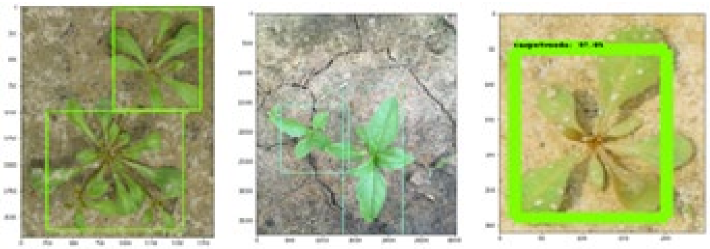

Figure 4: Detection of New Unseen Image

5. Conclusion and Future Work

Ultimately, a novel updated dataset for the detection of cotton and related weeds was proposed in this work. Using Label Img Tool, manually annotate the collected images. The two smallest sub datasets were then carefully chosen. Finally, MobileNet-SSD object detector was tested against various test images after being trained using the annotated images. The MobileNet-SSD object detector obtained an Average Precision for the detection task with an average of 70.1 % after 5000 iterations, according to the findings. In the future, any appropriate object detection techniques, such as YOLO, RCNN, etc., will be employed. Additionally, try the SSD with a greater amount of training images and iterations.

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